Refine Search

Search Results -

Terms	Documents
neural near network and training and weights and rescale	40

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L4

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	**Query**	**Hit Count**	**Set Name** result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L6 and spatial and neighborhoods	19

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L7

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
neural near network and spatial near error$	14

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
IBM Technical Disclosure Bulletins

Search: L9

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L9 and (scaling or rescal$)	5

Database:

US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
Derwent World Patents Index
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Search: L10

Refine Search

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Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L15 and predict$	48

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
JPO Abstracts Database
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Search: L16

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13
L12	neural near network same upscale	1	L12
L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5

L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L19 and scaling same error$	3

Database:

US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
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JPO Abstracts Database
Derwent World Patents Index
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Search: L20

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L20	L19 and scaling same error$	3	L20
L19	L18 and neural near network$	98	L19
L18	382/155,254,293,298.ccls.	2141	L18
L17	382/155,254,293,298	0	L17
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13
L12	neural near network same upscale	1	L12
L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8

L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L19 and rescale same error$	1

Database:
US Pre-Grant Publication Full-Text Database
US Patents Full-Text Database
US OCR Full-Text Database
EPO Abstracts Database
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Search: L21

Refine Search

Recall Text Clear Interrupt

Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L21	L19 and rescale same error$	1	L21
L20	L19 and scaling same error$	3	L20
L19	L18 and neural near network$	98	L19
L18	382/155,254,293,298.ccls.	2141	L18
L17	382/155,254,293,298	0	L17
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13
L12	neural near network same upscale	1	L12
L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9

L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L19 and rescale same error$	1

Database:

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Search: L21

Refine Search

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Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L21	L19 and rescale same error$	1	L21
L20	L19 and scaling same error$	3	L20
L19	L18 and neural near network$	98	L19
L18	382/155,254,293,298.ccls.	2141	L18
L17	382/155,254,293,298	0	L17
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13
L12	neural near network same upscale	1	L12
L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9

L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L22 and backpropagat$ and train$	24

Database: US Pre-Grant Publication Full-Text Database
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Search: L24

Refine Search

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Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L24	L22 and backpropagat$ and train$	24	L24
L23	L22 and back-propagating and train$	0	L23
L22	neural near network and normaliz$ with error$ and predict$	242	L22
L21	L19 and rescale same error$	1	L21
L20	L19 and scaling same error$	3	L20
L19	L18 and neural near network$	98	L19
L18	382/155,254,293,298.ccls.	2141	L18
L17	382/155,254,293,298	0	L17
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13
L12	neural near network same upscale	1	L12

L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

END OF SEARCH HISTORY

Refine Search

Search Results -

Terms	Documents
L24 and spatial	4

Database:
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Search: L25

Refine Search

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Search History

DATE: Wednesday, January 04, 2006 Printable Copy Create Case

Set Name side by side	Query	Hit Count	Set Name result set
	DB=PGPB,USPT,USOC,EPAB,JPAB,DWPI,TDBD; PLUR=NO; OP=OR		
L25	L24 and spatial	4	L25
L24	L22 and backpropagat$ and train$	24	L24
L23	L22 and back-propagating and train$	0	L23
L22	neural near network and normaliz$ with error$ and predict$	242	L22
L21	L19 and rescale same error$	1	L21
L20	L19 and scaling same error$	3	L20
L19	L18 and neural near network$	98	L19
L18	382/155,254,293,298.ccls.	2141	L18
L17	382/155,254,293,298	0	L17
L16	L15 and predict$	48	L16
L15	L14 and weights	60	L15
L14	L13 and scaling same error$	73	L14
L13	neural near network same scaling	341	L13

L12	neural near network same upscale	1	L12
L11	neural near network same rescale	1	L11
L10	L9 and (scaling or rescal$)	5	L10
L9	neural near network and spatial near error$	14	L9
L8	neural near network and spatial near errorS	4	L8
L7	L6 and spatial and neighborhoods	19	L7
L6	neural near network and training and weights and $scale and error$ and predict$	870	L6
L5	L4 and error$ and predict$	36	L5
L4	neural near network and training and weights and rescale	40	L4
L3	L1 and neural near network and training and weights	79	L3
L2	L1 and neural near network and training and weights and rescale	0	L2
L1	706/45	1483	L1

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Results for **"((neural <phrase> network <and> rescale)<in>metadata)"**
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((neural <phrase> network <and> rescale)<in>metadata)

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Display Format: Citation Citation & Abstract

» Key

IEEE JNL	IEEE Journal or Magazine
IEE JNL	IEE Journal or Magazine
IEEE CNF	IEEE Conference Proceeding
IEE CNF	IEE Conference Proceeding
IEEE STD	IEEE Standard

Select Article Information

1. **Robust control of nonlinear uncertain systems under generalized matchi using neuro-compensator**
Li Qingguo; Tong Shaocheng; Chai Tianyou;
American Control Conference, 1997. Proceedings of the 1997
Volume 3, 4-6 June 1997 Page(s):1556 - 1557 vol.3
Digital Object Identifier 10.1109/ACC.1997.610823
AbstractPlus | Full Text: PDF(140 KB) IEEE CNF

2. **Rescaling the energy function in Hopfield networks**
Xinchuan Zeng; Martinez, T.R.;
Neural Networks, 2000. IJCNN 2000, Proceedings of the IEEE-INNS-ENNS Int Conference on
Volume 6, 24-27 July 2000 Page(s):498 - 502 vol.6
Digital Object Identifier 10.1109/IJCNN.2000.859444
AbstractPlus | Full Text: PDF(344 KB) IEEE CNF

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Holmes, Michael B.

From:	Abdi, Aster (Chucach)
Sent:	Monday, January 30, 2006 10:51 AM
To:	Barnes, Crystal; Brown Jr., Nathan H.; Chang, Sunray; Datskovskiy, Sergey; Hartman, Ronald; Holmes, Michael B.; Norton, Jennifer L.; Patel, Ramesh; Pham, Thomas; Williams, Ronald; Chung, Eun Hee; Craig, Dwin; Guill, Russell L; Ochoa, Juan C.; Osborne, Luke R.; Pierre-Louis, Andre; Proctor, Jason S.; Sharon, Ayal; Stevens, Thomas H.; Thangavelu, Kandasamy; Bahta, Kidest; Cabrera, Zoila; Gandhi, Jayprakash; Garland, Steven; Jarrett, Ryan; Kasenge, Charles; Kosowski, Alexander; Lee, Doug; Masinick, Michael (AU 2125); Paladini, Albert; Rao, Sheela; Rapp, Chad; Rodriguez, Paul; Shechtman, Sean; Von-Buhr, Maria; Alhija, Saif A.; Basiaga, Dariusz; Day, Herng-Der; Ferris, Fred; Frejd, Russell; Gebresilassie, Kibrom K; Jones, Hugh; Lo, Suzanne; Luu, Cuong V.; Patel, Shambhavi K.; Phan, Thai; Saxena, Akash; Silver, David; Thornewell, Kimberly A.; Allen, Nicole L.; Bell, Meltin; Buss, Benjamin; Caldwell, Michael J.; Coughlan, Peter D.; Davis, George; Fernandez Rivas, Omar; Hirl, Joseph; Starks, Wilbert; Tran, Mai T.
Subject:	WORK GROUP MEETING REMINDER

-----Original Message-----

From:	Knight, Anthony
Sent:	Tuesday, January 17, 2006 12:29 PM
To:	Abdi, Aster (Chucach)
Cc:	Picard, Leo; Shah, Kamini; Vincent, David
Subject:	Work Group Meeting 1/30/06

We will be having a mandatory work group meeting on January 30th at 1:00 PM in the first floor conference room. Please adjust your schedules accordingly.

The SPE's of Work Group 2120

Terms used **neural network** **rescale**

Found **58** of **169,166**

Results 1 - 20 of 58

Result page: **1** 2 3 next

Relevance scale

1 Methods to speed up error back-propagation learning algorithm
Dilip Sarkar
December 1995 **ACM Computing Surveys (CSUR)**, Volume 27 Issue 4
Publisher: ACM Press
Full text available: pdf(1.86 MB) Additional Information: full citation, references, citings, index terms

Keywords: adaptive learning rate, artificial neural networks, conjugate gradient method, energy function, error back-propagation learning, feedforward networks, learning rate, momentum, oscillation of weights, training set size

2 Opening the neural network black box: an algorithm for extracting rules from function approximating artificial neural networks
Rudy Setiono, Wee Kheng Leow, James Y. L. Thong
December 2000 **Proceedings of the twenty first international conference on Information systems**
Publisher: Association for Information Systems
Full text available: pdf(206.40 KB) Additional Information: full citation, references, index terms

Keywords: decision rules, knowledge acquisition, neural networks

3 6-1 Visual perception & image processing: Multi-resolution image data fusion using 2-D discrete wavelet transform and self-organizing neural networks
Q. P. Zhang, M. Liang, W. C. Sun
June 2004 **Proceedings of the 2004 ACM SIGGRAPH international conference on Virtual Reality continuum and its applications in industry**
Publisher: ACM Press
Full text available: pdf(403.60 KB) Additional Information: full citation, abstract, references, index terms

In recent years, many solutions to multi-resolution image data fusion have been proposed; however, it is difficult to simulate the human ability of image fusion when algorithms of image processing are piled up merely. On the basis of the review of researches on psychophysics and physiology of human vision, this paper presents an

effective multi-resolution image data fusion methodology, which is based on discrete wavelet transform theory and self-organizing neural network, to simulate the process ...

Keywords: discrete wavelet transform, multi-resolution image data fusion, self-organizing neural network

4 Data mining with sparse grids using simplicial basis functions
Jochen Garcke, Michael Griebel
August 2001 **Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining**
Publisher: ACM Press
Full text available: pdf(808.88 KB) Additional Information: full citation, abstract, references, citings, index terms

Recently we presented a new approach [18] to the classification problem arising in data mining. It is based on the regularization network approach but, in contrast to other methods which employ ansatz functions associated to data points, we use a grid in the usually high-dimensional feature space for the minimization process. To cope with the curse of dimensionality, we employ sparse grids [49]. Thus, only $O(hn^{-1}n^{d-1})$ instead of ...

Keywords: approximation, classification, combination technique, data mining, simplicial discretization, sparse grids

5 The base-rate fallacy and the difficulty of intrusion detection
Stefan Axelsson
August 2000 **ACM Transactions on Information and System Security (TISSEC)**, Volume 3 Issue 3
Publisher: ACM Press
Full text available: pdf(124.41 KB) Additional Information: full citation, abstract, references, citings, index terms

Many different demands can be made of intrusion detection systems. An important requirement is that an intrusion detection system be effective; that is, it should detect a substantial percentage of intrusions into the supervised system, while still keeping the false alarm rate at an acceptable level. This article demonstrates that, for a reasonable set of assumptions, the false alarm rate is the limiting factor for the performance of an intrusion detection system. This is d ...

Keywords: base-rate fallacy, detection rate, false alarm rate, intrusion detection

6 Special issue on special feature: Use of the zero norm with linear models and kernel methods
Jason Weston, André Elisseeff, Bernhard Schölkopf, Mike Tipping
March 2003 **The Journal of Machine Learning Research**, Volume 3
Publisher: MIT Press
Full text available: pdf(164.22 KB) Additional Information: full citation, abstract, index terms

We explore the use of the so-called zero-norm of the parameters of linear models in learning. Minimization of such a quantity has many uses in a machine learning context: for variable or feature selection, minimizing training error and ensuring sparsity in solutions. We derive a simple but practical method for achieving these goals and discuss its relationship to existing techniques of minimizing the zero-norm. The method boils down to implementing a simple modification of vanilla SVM, namely vi ...

7 Data driven character animation: Style-based inverse kinematics
Keith Grochow, Steven L. Martin, Aaron Hertzmann, Zoran Popović
August 2004 **ACM Transactions on Graphics (TOG)**, Volume 23 Issue 3
Publisher: ACM Press
Full text available: pdf(428.46 KB) mov(23:16 MIN) Additional Information: full citation, abstract, references, citings, index terms

This paper presents an inverse kinematics system based on a learned model of human poses. Given a set of constraints, our system can produce the most likely pose satisfying those constraints, in real-time. Training the model on different input data leads to different styles of IK. The model is represented as a probability distribution over the space of all possible poses. This means that our IK system can generate any pose, but prefers poses that are most similar to the space of poses in the tra ...

Keywords: Character animation, Gaussian Processes, Inverse Kinematics, machine learning, motion style, non-linear dimensionality reduction, style interpolation

8 Learning one-dimensional geometric patterns under one-sided random misclassification noise
Paul W. Goldberg, Sally A. Goldman
July 1994 **Proceedings of the seventh annual conference on Computational learning theory**
Publisher: ACM Press
Full text available: pdf(1.00 MB) Additional Information: full citation, abstract, references, citings, index terms

Developing the ability to recognize a landmark from a visual image of a robot's current location is a fundamental problem in robotics. We consider the problem of PAC-learning the concept class of geometric patterns where the target geometric pattern is a configuration of k points in the real line. Each instance is a configuration of n points on the real line, where it is labeled according to whether or not it visually resembles the target pattern.

9 Poster papers: Non-linear dimensionality reduction techniques for classification and visualization
Michail Vlachos, Carlotta Domeniconi, Dimitrios Gunopulos, George Kollios, Nick Koudas
July 2002 **Proceedings of the eighth ACM SIGKDD international conference on Knowledge discovery and data mining**
Publisher: ACM Press
Full text available: pdf(897.67 KB) Additional Information: full citation, abstract, references, citings, index terms

In this paper we address the issue of using local embeddings for data visualization in two and three dimensions, and for classification. We advocate their use on the basis that they provide an efficient mapping procedure from the original dimension of the data, to a lower intrinsic dimension. We depict how they can accurately capture the user's perception of similarity in high-dimensional data for visualization purposes. Moreover, we exploit the low-dimensional mapping provided by these embeddin ...

10 Gravity: Fast placement for 3-D VLSI
Stefan Thomas Obenaus, Ted H. Szymanski
July 2003 **ACM Transactions on Design Automation of Electronic Systems (TODAES)**, Volume 8 Issue 3
Publisher: ACM Press
Full text available: pdf(199.32 KB) Additional Information: full citation, abstract, references, index terms

Three dimensional integration is an increasingly feasible method of implementing complex

circuitry. For large circuits, which most benefit from 3-D designs, efficient placement algorithms with low time complexity are required.We present an iterative 3-D placement algorithm that places circuit elements in three dimensions in linear time. Using an order of magnitude less time, our proposed algorithm produces placements with better than 11% less wire lengths than partitioning placement using ...

Keywords: 3-D VLSI, 3-D integrated circuits, Placement

11 Support vector machines: hype or hallelujah?
Kristin P. Bennett, Colin Campbell
December 2000 **ACM SIGKDD Explorations Newsletter**, Volume 2 Issue 2
Publisher: ACM Press
Full text available: pdf(1.26 MB) Additional Information: full citation, citings, index terms

Keywords: Support Vector Machines, kernel methods, statistical learning theory

12 Training hard to learn networks using advanced simulated annealing methods
Bruce E. Rosen, James M. Goodwin
April 1994 **Proceedings of the 1994 ACM symposium on Applied computing**
Publisher: ACM Press
Full text available: pdf(501.81 KB) Additional Information: full citation, references, index terms

Keywords: backpropagation, neural networks, optimization, simulated annealing

13 Introduction to Bayesian learning
Aaron Hertzmann
August 2004 **Proceedings of the conference on SIGGRAPH 2004 course notes GRAPH '04**
Publisher: ACM Press
Full text available: pdf(899.54 KB) Additional Information: full citation, abstract

Sophisticated computer graphics applications require complex models of appearance, motion, natural phenomena, and even artistic style. Such models are often difficult or impossible to design by hand. Recent research demonstrates that, instead, we can "learn" a dynamical and/or appearance model from captured data, and then synthesize realistic new data from the model. For example, we can capture the motions of a human actor and then generate new motions as they might be performed by that actor. B ...

14 Piriform (Olfactory) cortex model on the hypercube
J. M. Bower, M. E. Nelson, M. A. Wilson, G. C. Fox, W. Furmanski
January 1989 **Proceedings of the third conference on Hypercube concurrent computers and applications - Volume 2**
Publisher: ACM Press
Full text available: pdf(1.42 MB) Additional Information: full citation, abstract, references, citings, index terms

We present a concurrent hypercube implementation of a neurophysiological model for the piriform (olfactory) cortex. The project was undertaken as the first step towards constructing a general neural network simulator on the hypercube, suitable both for applied and biological nets. The method presented here is expected to be useful for a

class of complex and computationally expensive network models with long range connectivity and non-homogeneous activity patterns. The ...

15 Feature selection, L_1 vs. L_2 regularization, and rotational invariance
Andrew Y. Ng
July 2004 **Proceedings of the twenty-first international conference on Machine learning ICML '04**
Publisher: ACM Press
Full text available: pdf(192.52 KB) Additional Information: full citation, abstract, references

We consider supervised learning in the presence of very many irrelevant features, and study two different regularization methods for preventing overfitting. Focusing on logistic regression, we show that using $L1$ regularization of the parameters, the sample complexity (i.e., the number of training examples required to learn "well,") grows only *logarithmically* in the number of irrelevant features. This logarithmic rate matches the best known bounds for feature selection, a ...

16 Think globally, fit locally: unsupervised learning of low dimensional manifolds
Lawrence K. Saul, Sam T. Roweis
December 2003 **The Journal of Machine Learning Research**, Volume 4
Publisher: MIT Press
Full text available: pdf(2.91 MB) Additional Information: full citation, abstract, references, citings, index terms

The problem of dimensionality reduction arises in many fields of information processing, including machine learning, data compression, scientific visualization, pattern recognition, and neural computation. Here we describe locally linear embedding (LLE), an unsupervised learning algorithm that computes low dimensional, neighborhood preserving embeddings of high dimensional data. The data, assumed to be sampled from an underlying manifold, are mapped into a single global coordinate system of lowe ...

17 Analyzing human gait patterns for malfunction detection
Monika Köhle, Dieter Merkl
March 2000 **Proceedings of the 2000 ACM symposium on Applied computing - Volume 1**
Publisher: ACM Press
Full text available: pdf(357.35 KB) Additional Information: full citation, references, index terms

Keywords: Radial Basis Function networks, gait analysis, pattern classification

18 Sparse bayesian learning and the relevance vector machine
Michael E. Tipping
September 2001 **The Journal of Machine Learning Research**, Volume 1
Publisher: MIT Press
Full text available: pdf(999.88 KB) Additional Information: full citation, abstract, citings

This paper introduces a general Bayesian framework for obtaining sparse solutions to regression and classification tasks utilising models linear in the parameters. Although this framework is fully general, we illustrate our approach with a particular specialisation that we denote the 'relevance vector machine' (RVM), a model of identical functional form to the popular and state-of-the-art 'support vector machine' (SVM). We demonstrate that by exploiting a probabilistic Bayesian learning framewor ...

19 Session 5: novel interaction: MAUI: a multimodal affective user interface
Christine L. Lisetti, Fatma Nasoz
December 2002 **Proceedings of the tenth ACM international conference on Multimedia**
Publisher: ACM Press
Full text available: pdf(377.18 KB) Additional Information: full citation, abstract, references, citings

Human intelligence is being increasingly redefined to include the all-encompassing effect of emotions upon what used to be considered 'pure reason'. With the recent progress of research in computer vision, speech/prosody recognition, and bio-feedback, real-time recognition of affect will enhance human-computer interaction considerably, as well as assist further progress in the development of new emotion theories.In this article, we describe how affect, moods and emotions closely interact with co ...

Keywords: affect recognition, emotions, intelligent interfaces, interface agent

20 The importance of convexity in learning with squared loss
Wee Sun Lee, Peter L. Bartlett, Robert C. Williamson
January 1996 **Proceedings of the ninth annual conference on Computational learning theory**
Publisher: ACM Press
Full text available: pdf(566.87 KB) Additional Information: full citation, references, citings, index terms

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